Faculty Working Papers

THE MARKET MODEL: POTENTIAL FOR ERROR

Dennis J. Collins, Assistant Professor
Department of Accountancy
James C. McKeown, Professor, Department
of Accountancy

#606

College of Commerce and Business Administration
University of Illinois at Urbana-Champaign

Faculty Working Papers

HUMAN INFORMATION PROCESSING FOR DECISIONS TO INVESTIGATE COST VARIANCES

Clifton Brown, Assistant Professor, Department of Accountancy

#614

College of Commerce and Business Administration
University of Illinois at Urbana-Champaign

FACULTY WORKING PAPERS

College of Commerce and Business Administration

University of Illinois at Urbana-Champaign

October 10, 1979

Second Draft Not For Quotation

HUMAN INFORMATION PROCESSING FOR DECISIONS TO INVESTIGATE COST VARIANCES

Clifton Brown, Assistant Professor, Department of Accountancy

#614

Summary:

The principal focus of this paper is manager cost variance investigation decisions. A conceptual framework is developed which predicts the effects of situational variables upon a manager's efficiency in cost variance information processing and in cost variance investigation decision making. This framework is based, in part, upon the psychological concepts of signal detection and heuristic decision strategy. A simulation is used to derive some implications from the conceptual framework and a laboratory experiment is conducted to test these implications. Overall, the implications were supported by the experimental results. An ex post hypothesis is introduced as a potential explanation for the deviations from expectations.

HUMAN INFORMATION PROCESSING FOR DECISIONS
TO INVESTIGATE COST VARIANCES

An important aspect of some control processes is the analysis and investigation of standard cost variances provided within accounting reports. A substantial portion of the accounting literature on variance investigation has employed the normative model approach—researchers have created variance investigation models which a manager should use. Rarely has attention been given to how the manager would interpret and integrate information required by the various normative models.

The principal focus of this paper is on the effects of situational variables upon a manager's information processing for purposes of making variance investigation decisions. The specific objectives are 1) to develop a conceptual framework which will predict effects of specific situational variables on a manager's relative efficiency in information processing and in variance investigation decision making and 2) to empirically test some implications of this conceptual framework.

The vari~~ous~~ANCE investigation literature contains a paucity of research relating to the manager's ability and efficiency to interpret and integrate the information being provided within accounting variance reports or being proposed for inclusion within these reports by the literature.[1] The literature is concerned mainly with modeling the investigation significance of variances. Some modeling approaches described within the literature include the Skewhart $\overline{X}$ chart procedure (Probst, 1971; Koehler, 1968; Luh, 1968; Jeurs, 1967; Zannetos, 1964), classical statistics incorporating investigation costs and benefits (Bierman et al., 1961), the cumulative sum and economic cumulative sum procedure (Kaplan, 1975;

Jacobs, 1978), and decision theory (Kaplan, 1969; Dyckman, 1969; Kaplan, 1975; Dittman and Prakash, 1978). As this literature has expanded the information requirements of the proposed variance investigation models have become diverse and complex. However, to the extent that not all the parameters are operationalizable (given either cost or utilization constraints), the manager must continue to make the variance investigation decisions using the information provided by the accountant and by his own experience.

A manager's variance investigation decision may be viewed as the culmination of a two-stage process. The first stage concerns the detection of the particular distribution (e.g., in-control or out-of-control[2]) that generated the variance. The manager's performance of this task is a function of the sensitivity of his decision process (model). The second stage concerns the manager's investigation decision criteria. Having arrived at a conclusion (albeit probabilistic) about the distribution that generated the variance, the manager must integrate and process various objective function parameters in order to arrive at his variance investigation decision.

Although the variance investigation decision process has been described as two stages, the manager may not actually utilize such a sequential stage process. A manager's actual decision process can be labeled a heuristic, a learned set of rules or principles. However, the sequential stage process will facilitate the identification of variables which can affect both the variance investigation decision process and the results of the process.

General Conceptual Development

The manager's decision concerning the nature of a given variance is analogous to a decision concerning the presence of a signal in a background of noise. The background of noise is represented by the serial distribution of variances generated by a production system that is operating within an in-control state. The signal is represented by an observed variance generated by a system that has changed and is currently operating within an out-of-control state. The general problems confronting the manager ARE ~~is~~ that he must decide which state of control is most probable based upon some incomplete set of information and he must decide whether to investigate a variance based upon some subjective decision criteria.

When a manager deals repetitively with a similar situation the variables affecting his long-run decision efficiency can be identified utilizing the sequential stage process described earlier. The sensitivity of the manager's decision process can be affected by the structure of the decision situation and by his knowledge of this structure. The manager's knowledge of the situation is affected by the available information (both provided by the variance report and provided from other sources) and by his ability to learn from his experiences with the production system.

The variables which can affect both the manager's investigation decision process and the results of his process include: 1) the structure of the decision situation, 2) the contents of the available information set, 3) the manager's information processing efficiency, and 4) the manager's learning efficiency. The structure of the particular

decision situation primarily depends upon the number of possible states of nature, the relative frequencies of the states, the various statistical relationships among the states, and the relationships between the various decision outcomes (the costs incurred given a specific decision and the existence of a specific state). The contents of the available information set refers to the information known by the individual prior to his decision, either information that specifically relates to the current decision or information that relates to the statistical relationships among the states of nature. The individual's efficiency in processing the available information relates to the particular heuristics or strategies employed in combining and weighting the various items of information. The individual's decision and information processing performance can be evaluated by comparing his performance against that of an optimal model under similar conditions as the individual. Within this research the optimal decision rule is assumed to be the minimization (maximization) of the expected cost (value) of a series of investigation decisions. The individual's learning efficiency refers to his ability to expand the available information set over time. Such learning can occur through improved estimates of unknown items of statistical information and through modifications of information processing strategies to incorporate state relationships which were unknown or undetected previously.

The objective and method utilized in this study require some comments on two concepts: signal detection theory and human information processing. The relationships between physical and psychological scales

of measurement are part of the domain of psychophysics. Modern psychophysics adopts the view that subjects can make meaningful evaluations of the magnitudes of their sensory experiences and therefore sensory magnitudes, as well as physical magnitudes, can be quanitifed. One approach of modern psychophysics is based upon the theory of signal detection (TSD). TSD permits the separation of the decision maker's ability to discriminate between classes of stimuli (sensitivity) from his motivational response biases (decision criteria).[3] Traditionally, psychophysics has employed TSD to study perceptual processes; i.e., sensory processes such as audition and vision. Over the last decade, however, TSD has been applied to conceptual processes.[4]

The basic TSD experiment utilizes the single-interval procedure which consists of a series of trials, each trial comprised of an observation interval and a response interval. The possible stimulus events during the observation interval are: 1) the observation contains a meaningful signal added to a background of noise (sn trial) or 2) the observation contains only a background of noise (n trial). It is assumed that trials are pairwise independent and that the prior probabilities of n and sn are given and remain constant. The background noise fluctuates at random from trial to trial; the stimulus, usually a fixed level, is added to the noise. The task of the subject is to detect which distribution (sn or n) generated the observation.

On any trial in the basic experiment there exist four possible outcomes of the subject's decision (either "Yes, a signal was presented" or "No, a signal was not presented") in conjunction with the actual distribution (either sn was presented or n was presented). A 2 x 2 conditional

probability matrix for a series of these events can be determined using observed response frequencies.[5] All parameters of the TSD model are derived from this conditional probability matrix.

Given a single-interval task and an objective function such as the maximization of expected value, a 2 x 2 payoff matrix of these values can be specified where each value relates to one of the event outcomes. For example, the subjective value related to the event outcome of saying "Yes" and sn actually being present would be V(Y,sn). The decision rule for maximizing the expected subjective value is to say "Yes" when:

$$\frac{P(x|sn)}{P(x|n)} > \frac{P(n)}{P(sn)} \cdot \frac{V(N,n) - V(Y,n)}{V(Y,sn) - V(N,sn)}, \qquad \text{Equation 1}$$

where x represents an observed stimulus, Y is yes, N is no, and n and sn are defined as before. An equality of terms in Equation 1 means indifference. This point can be considered the critical value of the likelihood ratio of the observations, $L(x_o)$, which, for this decision rule, has two possible values: 1) a theoretical value which is a measure of the criteria of an optimal (or ideal) subject and 2) a subjective value which is a measure of the criteria of an actual subject.

The parameter which measures individual discrimination sensitivity (d') is defined as follows:[6]

$$d' = \frac{\mu_{sn} - \mu_n}{\sigma} = z_n - z_{sn}, \qquad \text{Equation 2}$$

where μ_i = the mean of the ith distribution (either sn or n);

σ = the standard deviation of both distributions;

z_i = the value of the normal distribution function associated with the ith distribution (either sn or n) and any decision axis cutoff value common to both distributions.

The parameter which measures individual decision criteria, β, is defined as:

$$\beta = \phi(z_{sn}) \;/\; \phi(z_n) \,, \qquad \text{Equation 3}$$

where $\phi(\;)$ denotes the normal density function for the value in parentheses. Graphic representations of the TSD parameters are presented in Figure 1.

Insert Figure 1 about here

Of particular interest here from the literature on HIP is the anchoring and adjustment heuristic.[7] In many situations, individuals first make decisions by starting with an initial anchor (decision point) and then adjust this initial anchor as they learn from their experiences. The initial anchor can be suggested by the structure of the decision situation, or can be the result of a partial computation or estimate. However, empirical tests involving the anchoring and adjustment heuristic indicate individuals do not sufficiently adjust their initial decision point. That is, their adjustment is less than that which would allow optimal processing of the available information (Slovic and Lichtenstein, 1971; Slovic, 1972; Alpert and Raiffa, 1968; Tversky and Kahneman, 1974).

Research Methodology and Design

Two general methods are employed in this reserch—simulation and laboratory experimentation. The major objective of the simulation is to produce patterns which would assist in predicting the behavior of human decision makers within the decision situation under study. The major objective of the laboratory experiment is to test the conceptual development through the hypotheses derived by the simulation. Both parts of the study deal with the same task and variables.

Experimental Environment and Task

The standard cost variance investigation studied within this research was set in an environment of a manufacturing company. More specifically, the subjects were asked to assume the role of the operational manager of an assembly department which assembles a single product, a metal folding chair. The operating efficiency of the assembly department is determined completely by the labor efficiency of the assembly workers. The labor efficiency standard (stated in terms of time per unit assembled) was based on engineering estimates that allowed for unavoidable labor inefficiencies and reasonable variation in worker performance (i.e., the standards were currently attainable). The subjects were instructed to accept the labor efficiency standard as fair in terms of control and performance goals. The physical labor process of the department could be in only one of two mutually exclusive states of nature; either in-control or out-of-control.

The subjects were 86 senior year undergraduate and master's level graduate students enrolled in the business college at a large state university. The subjects participated in the experiment during a two week period; 47 participated in the first week and 39 participated in the second week. A total of 92 subjects initially volunteered to participate but six subjects failed to complete the experiment. The 86 subjects who completed the experiment consisted of 63 males and 23 females.[8]

Each subject received a sequential series of standard cost variance reports and was asked for each report to decide whether to investigate or not to investigate the reported labor efficiency variance. Two

assumptions were provided to aid the subject's decision making process. First, if they decided to investigate a variance and the labor process turned out to be out-of-control, the process would be returned to the original in-control state with certainty. Second, if they decided not to investigate a variance and the labor process was out-of-control, the process would remain out-of-control with certainty.

Each standard variance report was concerned with the results of a single job-order to produce a constant number of chairs and reported only aggregate (overall assembly department) results. Each report contained the aggregate standard assembly time allowed per chair, the actual assembly time incurred per chair, the overall labor efficiency variance per chair, the total number of chairs produced, and the estimated costs associated with each possible decision in combination with each possible state of control. All time units were presented in minutes. The actual assembly time and the labor efficiency variance contained in a variance report were conditionally independent of those contained in previous variance reports.

The subjects were told that their immediate supervisor, the product section manager, would evaluate their control performance in terms of minimization of both investigation and production costs above the expected standard. A cash bonus was promised to the subjects, the size of the bonus being contingent upon the extent to which they minimized these costs. The measure of a subject's control performance was determined by summing his total investigation decision costs over the series of variance reports and dividing this sum by the sum of the total investigation decision costs incurred by an optimal model over the same series

of variance reports. The subject's cash bonus was inversely related to this measure. The minimum bonus was set at $2.00 and the maximum at $10.00.

The experiment was conducted in two phases—a training phase and an experimental phase. The training phase consisted of three contiguous sessions in which the subject learned the role and presumably developed a decision strategy. Performance feedback was given at the completion of each training session. The experimental phase consisted of a single session in which the subject received a series of variance reports similar to those presented in the training session. In this phase no performance feedback was given until after the completion of the entire experiment.

Selection and Operationalization of Variables

Three independent variables, each measured using a dichotomous classification, were employed: 1) the information variable, 2) the distribution variable, and 3) the cost variable. Individual process variables, measured on a continuous scale, included 1) individual decision model sensitivity and 2) individual decision criteria. The major dependent variable was individual long-run decision efficiency (in terms of incurred costs). The general research design, presented in terms of dependent and independent variables, is depicted in Table 1.

Insert Table 1 about here

The information variable. The effects of the contents of the available information set are studied by manipulating the presence and absence of certain distributional information. The first level, labeled I1, is derived from the set of information assumed to

come from the individual's experience with the system. It includes: 1) the portion of time in which the process had been found to fall in each of the two states, 2) the assumption that the random variable of interest (actual minutes incurred per chair or its associated standard variance) is normally distributed in either state, 3) the lowest and highest past observed values of the random variable, and 4) the minimum and maximum past costs associated with each state. The second level of the information variable, labeled I2, additionally included the mean and the standard deviation of the random variable within each state.

The distribution variable. The effects of the statistical structure of the decision are studied by manipulating a distributional information variable. Since the difficulty of the discrimination task increases as the area of distributional overlap between the two states increases (see Figure 1), one level of the distribution variable had a greater area of overlap than the other.

Manipulation of the distribution variable involved two factors: 1) the distributional parameters of each state and 2) the statistical relationship between the states. The two levels of this variable are generated through a change in the variance and in the standardized distance between the means of the two states. A given set of parameters and relationships were assumed for the first level of the distribution variable, labeled S1. These are:

1) μ_{11} = 36.0 actual minutes incurred per chair;

2) $\sigma_{11} = \sigma_{12} = \sigma_1$ = 3.0 actual minutes incurred per chair; and

3) $\mu_{12} = \mu_{11} + 1.5\sigma_1 = 40.5$ actual minutes incurred per chair;

where μ_{ij} = the mean of the jth state of control (in-control = 1 and out-of-control = 2) given the ith distribution level (S1 = 1 and S2 = 2); and

σ_{ij} = the standard deviation of the jth state of control given the ith distribution level.

The second level of the distribution variable, labeled S2, had the following parameters and relationships:

1) $\mu_{21} = 36.0$ actual minutes incurred per chair;

2) $\sigma_{21} = \sigma_{22} = \sigma_2 = 5.0$ actual minutes incurred per chair; and

3) $\mu_{22} = \mu_{21} + 1.8\sigma_2 = 45.0$ actual minutes incurred per chair;

where μ_{ij} and σ_{ij} are defined the same as in the S1 level.

The cost variable. Since the importance of the discrimination task increases as the costs associated with decision outcomes that involve different decision errors diverge, the different levels of the cost variable will be associated with different decision error costs. One level of the cost variable is structured in favor of more variance investigations and the other level of the cost variable is structured in favor of fewer variance investigations. Given the two possible states of control and two possible decisions, there follows that two types of errors can be made in reaching a decision: the decision to investigate when the in-control state exists and the decision not to investigate when the out-of-control state exists. Each level of the cost variable takes one of the following forms: 1) the marginal cost of a decision not to investigate when the out-of-control state exists equals three times the

marginal cost of a decision to investigate when the in-control state exists (labeled level C1) and 2) the reverse of the C1 level decision error cost relationships (labeled level C2).

Individual decision model sensitivity. The sensitivity of the individual's decision model relative to the decision situation is measured using a function of the TSD parameter d'. For an individual i, an empirical estimate of d' is obtained using the individual's conditional probabilities P(investigate | out-of-control) and P(investigate | in-control) to calculate a subjective z_1 and z_2. If d'_k is generated by using optimal model k, then the empirical d'_i would fall below d'_k due to: 1) individual inconsistency in the use of the cutoff value (employing a variable response range) or the individual makes one or more temporary processing errors and 2) the individual utilizes more than one cutoff value.

Based upon an analysis of each individual's decisions, d'_i can be adjusted for the effects of using multiple cutoff values. Defining d'^a_i to be the individual's decision model sensitivity after eliminating the effects of multiple cutoff values:

$$DNA_i = d'^a_i \;/\; d'_k . \qquad \text{(Equation 4)}$$

As the range around the individual's cutoff value (within which decisions are not made using a strict relation to this cutoff value) approaches zero, the variable DNA_i approaches a value of one.

Individual decision criteria. The criteria the individual adopts in making decisions are measured using a function of the TSD parameter β.

An empirical estimate for the β of an individual, labeled β_i, is obtained using the z_1 and z_2 values associated with the individual's conditional probabilities employed in estimating d_i'. The measure β_i is relative to the decision situation. The β_i measure diverges from the value of β_k (generated using optimal model k) as the result of several factors: 1) the individual does not process properly the effects of the relative costs of the two types of decision errors, 2) the individual does not process properly the effects of the relative frequencies of the two states, and 3) the individual uses more than one cutoff value.

As before, the β_i measure can be adjusted for the effects of multiple cutoff values (labeled β_i^a). A measure derived from the β_i^a variable can be considered a measure of individual anchoring bias. In this study, anchoring bias refers to the incomplete adjustment from an initial decision anchor towards the optimal cutoff value. Since the measure is dependent on the direction of adjustment it is conditional upon the level of the cost variable. Using BNC_i to denote the extent of an individual's anchoring bias:

$$BNC_i|C1 = (\beta_i^a - \beta_k)/\beta_k, \text{ and}$$
$$BNC_i|C2 = (\beta_k - \beta_i^a)/\beta_k. \qquad \text{(Equation 5)}$$

BNC_i becomes larger as the extent of anchoring bias increases, and approaches a value of zero as the extent of anchoring bias decreases.

Individual long-run decision efficiency. A major dependent variable of interest in this research is the cost incurred as a result of the individual's variance investigation decisions. The experimental objective function for all decision situations is to minimize these costs.

Since absolute investigation decision costs are not comparable between decision situations, a relative measure was used. Denoting such a measure G_{ij} it is computed as:

$$G_{ij} = (IC_{ij} - MC_{kj}) \;/\; SMC_k \,, \qquad \text{(Equation 6)}$$

where IC_{ij} = individual i's investigation decision cost for decision j;

MC_{kj} = optimal model k's investigation decision cost for decision j; and

SMC_k = the sum of optimal model k's investigation decision costs over all decisions (m in number).

The G_i measure is the additional cost of the decisions made by individual i above the cost of the decisions made by optimal model k as a percentage of the total cost of the optimal model's decisions. This measure is computed as:

$$G_i = \sum_{j=1}^{m} G_{ij} \,. \qquad \text{(Equation 7)}$$

The lower the G_i value, the higher the decision efficiency of the ith individual.

Simulation and Hypotheses Formation

Two general types of simulations are performed—simulation of optimal model performances and simulation of subjective investigation decision performances.

Simulation of Optimal Model Performances

Optimal model performance is simulated for each treatment condition involving the information, distribution, and cost variables. For each

of the k treatment conditions ($k = 1,8$), the outputs of the simulation are the optimal measures of decision sensitivity, d'_k, decision criteria, β_k, and investigation decision cost for each of j decisions, MC_{kj}. The simulation is based upon various assumptions and restrictions. First, the form of the optimal model is that represented by equation 1. Second, the labor efficiency variance reports used in the simulation of optimal model performance are the same as those presented to the subjects in the laboratory experiment. Finally, the information available to the optimal model is the same made available to an individual within the given treatment condition. Within one level of the information variable the available information set does not contain all the parameters required to fit the optimal model. Therefore, within this level the optimal model must use the training session data to estimate the missing parameters.

Simulation of Subjective Model Performances

Subjective model performance is simulated for each treatment condition involving the information, distribution, and cost variables. The simulation of subjective model performances is accomplished in two stages. The first stage simulates the post-training subjective decision heuristic. The second stage simulates the main experiment subjective performance measures.

The first stage of simulation is based upon various assumptions and restrictions. First, the subjects will behave as if they use the anchoring and adjustment heuristic during the training phase of the experiment. Second, the pre-training decision anchor will be located at a central point between the means of the two states of control.[9] Finally, the subjective adjustment processes will be approximately equal

over the treatment conditions. Due to the anchoring and adjustment assumption, the subjective adjustment process is defined as a linear movement along the standard cost variance axis from the initial decision anchor towards the appropriate optimal decision cutoff.[10] For each of the i treatment conditions (i=1,8) the output of the first stage of simulation is the subjective decision heuristic (the variance cutoff value used to make investigation decisions).

The second stage of the simulation is based upon the assumption that the subjective decision cutoff values obtained in the first stage will be consistently used in making the variance investigation decisions within the main experiment. For each of the i treatment conditions, the outputs of the second stage of simulation are the subjective model decision criteria, β_i^a, and the subjective model investigation decision cost for each of j decisions, IC_{ij}.

The performance measures obtained from the optimal model and subjective model simulations will be combined (using Equations 5, 6, and 7) to form simulated BNC_i and G_i measures for each treatment combination.

Hypotheses Formation

The DNA_i (Equation 4) variable, which measures the relative deviation of the individual's decision model sensitivity from that of the optimal model's, is due generally to individual decision inconsistencies (a variable response range) and temporary processing errors, and should be unrelated to the independent variables. If individuals are randomly assigned to the specific decision situations there is no a priori reason to expect that significant differences in this measure are due to the variations in the independent variables.

The effects of the independent variables on the measure of individual decision sensitivity can be hypothesized as follows:

H1.1 $(\overline{DNA_i}|I1) = (\overline{DNA_i}|I2)$.

The information variable will have no significant effect on the subjects' relative decision model sensitivity.

H1.2 $(\overline{DNA_i}|S1) = (\overline{DNA_i}|S2)$.

The distribution variable will have no significant effect on the subjects' relative decision model sensitivity.

H1.3 $(\overline{DNA_i}|C1) = (\overline{DNA_i}|C2)$.

The cost variable will have no significant effect on the subjects' relative decision model sensitivity.

The variable of individual anchoring bias, BNC_i, was simulated by combining the output of the optimal model simulation, β_k, and the output of the subjective model simulation, β_i^a, where i and k are the unique treatment conditions (both i and k = 1,8). The definition of the BNC_i variable is the same as described above (Equation 5). The results of this combination process were averaged over all conditionals except for the independent variable of interest.[11] Potentially significant main effects of an independent variable were identified by comparing the difference between the average BNC_i given the levels of the independent variable to the standard error of their estimates. This procedure resulted in identifying one independent variable with a potentially significant main effect, the cost variable.[12] The main effect suggests that the individual anchoring bias will be greater when given the C2 cost variable level than when given the C1 level. Given the assumptions of the subjective model simulation, the more extreme the optimal

cutoff relative to the assumed initial cutoff (anchor) the greater should be the individual anchoring bias. The treatment conditions with the most extreme optimal cutoffs are those within the C2 cost level.

The hypotheses concerning the effects of the independent variables upon individual anchoring bias can be summarized as follows:

H2.1 $(\overline{BNC}_i | I1) = (\overline{BNC}_i | I2)$.

The information variable will have no significant effect on the subjects' anchoring bias.

H2.2 $(\overline{BNC}_i | S1) = (\overline{BNC}_i | S2)$.

The distribution variable will have no significant effect on the subjects' anchoring bias.

H2.3 $(\overline{BNC}_i | C1) < (\overline{BNC}_i | C2)$.

The anchoring bias of those subjects within the C1 cost level will be significantly smaller than that of those subjects within the C2 level.

The individual long-run decision efficiency variable, G_i, was simulated by combining the output of the optimal model simulation, MC_{kj}, and the output of the subjective model simulation, IC_{ij} where k and i are the unique treatment conditions. The definition of the G_i variable is the same as described above (Equation 7). The results of this combination process were averaged over all conditionals except for the independent variable of interest. Potentially significant main effects of an independent variable were identified by the same techniques used for the individual anchoring bias variable. This procedure resulted in identifying one independent variable with a potentially significant main effect, the cost variable.[13] This main effect suggests that individual

long-run decision efficiency will be greater when given the C1 cost level than when given the C2 level.

The results of this combination process were extended by averaging over all conditionals except for pairs of independent variables of interest. Potentially significant interaction effects of a pair of independent variables were identified using the same techniques as described above. This procedure resulted in identifying one interaction with a potentially significant effect, the cost by distribution variables.[14] This interaction suggests that the distribution variable is effective at one level only of the cost variable (the C2 level).

Given the above discussion the effects of the independent variables on the G_i measure can be hypothesized as follows:

H3.1 $(\overline{G}_i|C1) < (\overline{G}_i|C2)$.

Those subjects within the C1 cost level will have significantly greater relative decision efficiency than will those subjects within the C2 level (recall there is an inverse relationship between G_i and decision efficiency).

H3.2 $(\overline{G}_i|S2) < (\overline{G}_i|S1)$.

Those subjects within the S1 distribution level will have smaller relative decision efficiency than will those subjects within the S2 level. Significance is not predicted due to the interaction effect with the cost variable.

H3.3 $(\overline{G}_i|I1) = (\overline{G}_i|I2)$.

The information variable will have no significant effect on the subjects' relative decision efficiency.

H3.4 $[(\overline{G}_i|S1,C1) - (\overline{G}_i S2,C1)] < [(\overline{G}_i|S1,C2) - (\overline{G}_i|S2,C2)]$.
There will be a significant interaction of the distribution and cost variables in which the distribution variable will have no significant effect given the C1 cost level but will have a significant effect given the C2 cost level.

The Experiment

Experimental Materials

The experimental materials included a background information booklet, variance investigation decision stimuli, and a motivation questionnaire.[15]

Background information. A background information booklet was designed to provide the subjects with a common experimental environment. The booklet provided the subject with general company information, general product information, general manufacturing process information, and specific assembly department information. The specific assembly department information included information concerning the employees, the physical process, the accounting control system, the subject's task as the operational manager, and the subject's performance evaluation as the operational manager.

Variance investigation decision stimuli. Each variance investigation decision trial consisted of the presentation of a labor efficiency variance report and a subject's response to two questions. The questions were: 1) would you investigate this reported variance, and 2) how strongly do you feel about your decision? During the training phase each decision trial was followed by feedback concerning the actual state

of the assembly line and the actual costs incurred for each possible decision given the actual state. Decision trials were presented in booklets of 33 trials (each trial included the report with questions followed by the feedback). Within the experimental phase decision trials were presented in booklets of 50 trials (each trial included only the report with questions).

An example of a labor efficiency variance report with the set of questions is presented in Appendix A. The format of the report and questions was constant for all treatment conditions. Various information constant over all decision trials within a treatment condition were presented on a separate page prior to the start of the decision trials.

Elicitation of subject motivations. Subject motivations were elicited using a motivation questionnaire developed by Snowball and Brown (1977). The questionnaire is a ten item Likert-type scale which has submeasures for both intrinsic and extrinsic motivation.

<u>Experimental Procedures</u>

Experimental procedures included assignment of subjects to treatment conditions, administration of a training phase, administration of an experimental phase, and final debriefing.

Assignment of subjects to treatment conditions. Since each of the 86 subjects was assigned to one of eight groups, randomization per se could not be relied upon to control for individual attribute differences between groups. An alternative is to block the randomization process on individual attribute dimensions assumed to significantly affect the subject's information processing within the task required by the experiment.

In the present study, the randomization process of assigning subjects to treatment conditions was blocked on individual intelligence.[16] Those subjects with a GPA above the median for all subjects were categorized as above average intelligence and those subjects with a GPA below the median were categorized as average intelligence. Each subject within an intelligence category then was assigned randomly to one of the treatment conditions with the restriction that each intelligence group contributed an equal number of subjects to each condition.[17] Upon assignment to a treatment condition each subject received the background information booklet.

Training phase. Each subject received training within the treatment condition to which he was assigned. Training was conducted in groups of two subjects within a 50 minute session administered by either the experimenter or by an experimental assistant. Training of all subjects (within each week) was completed over two contiguous days. The decision trials with feedback were presented in three booklets of 33 trials, and additional performance feedback was given at the completion of each booklet. This additional feedback was the the performance measure upon which the subject's payment would be based when in the main experiment.

Experimental phase. The experimental session lasted one hour and was administered by the experimenter. The experimental phase (within each week) was completed over two contiguous days immediately following the training phase.

The experimental session consisted of two parts. The first part was the sequential presentation of 100 decision trials, the completion

of which twenty minutes were allowed. The second part of the experimental phase was the administration of the motivation questionnaire.

Final debriefing. Each subject's final performance measure for the variance investigation decisions part of the experimental phase was presented individually at a later date. At this time cash payment was determined, the subject was debriefed as to the purpose of the experiment, and any questions were answered.

Analyses and Results

The method of analysis employed is analysis of variance using the model comparison procedure (Appelbuam and Cramer, 1974; Lewis and Keren, 1977). This method of analysis was selected due to the nonorthogonality of the data structure. The problem of nonorthogonality arises in this instance as a result of non-equal cell frequencies.

The model comparison procedure involves fitting a linear model allowing for certain effects, and then comparing the obtained fit to that of a linear model which omits one or more of the effects. The objective is to find the simplest model that adequately fits the data. The procedure begins with the complete or full model (which allows for all effects) and eliminates effects starting with the highest order interactions. The F test as described by Lewis and Keren (1977) is used to test the fit of the various models.

Given a dependent variable, after the simplest (or reduced) model is found the sources of this model are presented with their corresponding F values. These source F values are the same as model comparison F

values where the comparison models are the reduced model and the reduced model without the corresponding source.

Unless otherwise specified all 2-way interactions are tested against the without 3-way interaction model, employing the assumption that the 3-way interaction effect is equal to zero within the subject population. All individual attributes are retained in each model, employing the assumption that these effects are not necessarily equal to zero within the subject population.

Relative Decision Model Sensitivity

Hypotheses 1.1, 1.2, and 1.3 relate to the adjusted relative deviation of the individual's decision model sensitivity from optimal sensitivity. The method of analysis is the model comparison procedure where the dependent variable is the DNA_1 measure. The independent variables are the three situation variables (with their interactions), the three motivation factors, and the GPA variable.

The model comparison procedure results and the F values associated with the sources of the reduced model are presented in Table 2. The reduced model contains the cost variable (significant at ~~the~~ $p<.01$ ~~level~~) and the intrinsic motivation factor (significant at ~~the~~ $p<.10$ ~~level~~). Means, variances, and sample sizes of the dependent variable given the levels of the significant situation variable are included in Table 2. Using the F test of equal variances, the variances between the levels of the cost variable differ significantly ($F=2.57$, $p<.01$).

The no difference predictions of both hypotheses 1.1 and 1.2 are confirmed by the results. However, hypothesis 1.3 which predicted no

difference between $(\overline{DNA_i}|C1)$ and $(\overline{DNA_i}|C2)$ was not confirmed. The C1 cost level has a significantly larger mean ($p<.01$).

Insert Table 2 about here

Relative Anchoring Bias

Hypotheses 2.1, 2.2 and 2.3 relate to the effect of anchoring bias on relative individual decision criteria. The method of analysis is the model comparison procedure where the dependent variable is the BNC_i measure and the independent variables are the three situation variables (with their interactions), the three motivation factors, and the GPA_i variable.

The model comparison procedure results and the F values associated with the sources of the reduced BNC_i model are presented in Table 3. The results indicate that the reduced BNC_i model contains the cost variable (significant at $p<.05$), the extrinsic (monetary) motivation factor (significant at $p<.01$), and the GPA_i variable (significant at $p<.05$). The means, variances, and sample sizes of the BNC_i measure given the levels of the cost variable are included in Table 3. Using the F test of equal variances, the variances of the BNC_i given the levels of the cost variable differ significantly ($F=9.36$, $p<.01$).

The no difference predictions of both hypotheses 2.1 and 2.2 are confirmed by the results. Hypothesis 2.3 predicted that $(\overline{BNC_i}|C1)$ would be significantly smaller than $(\overline{BNC_i}|C2)$ and the model comparison procedure indicates that the difference is significant ($p<.05$). However, the results are the opposite of the prediction, with the C2 level having the smaller mean.

Insert Table 3 about here

Individual Long-Run Decision Efficiency

Hypotheses 3.1, 3.2, 3.3. and 3.4 relate to the decision costs incurred by the individuals relative to the decision costs incurred by the optimal models. The method of analysis was the model comparison procedure where the dependent variable is the G_i measure. The independent variables are the three situation variables (with their interactions), the DNA_i variable, the three motivation factors, and the GPA_i variable. Ideally, both the DNA_i and the BNC_i variables should be included in the model; however, the BNC_i variable had significantly greater association with the other independent variables than did the DNA_i variable (the R^2 for the full BNC_i model was 0.6474, whereas the R^2 for the full DNA_i model was 0.2192).

The model comparison procedure results and the F values associated with the sources of the reduced model are presented in Table 4. The results indicate that the reduced G_i model contains the distribution by cost interaction (significant at p<.01) and the DNA_i variable (significant at p<.01). The means, variances, and sample sizes for the distribution by cost interaction within the G_i model are included in Table 4. Bartlett's test for homogeneity of variances indicates that the variances within the G_i model distribution by cost interaction are significantly heterogeneous (χ^2=10.66, p<.05 with 3 d.f.).

Hypothesis 3.4 predicted a significant distribution by cost interaction within the G_i model in which $(\overline{G}_i|S1,C1)-(\overline{G}_i|S2,C1)$ would be

smaller than $(\overline{G}_i|S1,C2)-(\overline{G}_i|S2,C2)$. The results of the model comparison procedure confirm this hypothesis. Hypothesis 3.1 predicted that $(\overline{G}_i|C1)$ would be significantly smaller than $(\overline{G}_i|C2)$ and hypothesis 3.2 predicted that $(\overline{G}_i|S2)$ would be smaller than $(\overline{G}_i|S1)$. Both hypotheses are confirmed by the results. Hypothesis 3.3. predicted that $(\overline{G}_i|I1)$ would not differ significantly from $(\overline{G}_i|I2)$, and the results indicate that the difference was not significant.

Insert Table 4 about here

Discussion of Results

Overall Results

First, variable response ranges were smaller and decision anchoring biases were larger within situations where the adjustment process involved convergence toward the standard. Although these effects were contrary to those predicted, the concept of a subjective adjustment limit provides a plausible explanation. If this phenomenon exists it would affect both the variable response range and the decision anchoring biases in the same manner as the obtained results.

Second, the obtained effects of the situation variables on the relative decision costs were weaker than those predicted. The predicted effects were based, in part, upon the assumption of equal learning efficiency between the levels of the various situation variables. However, the obtained learning efficiencies were not equal between various situation variable levels. Incorporation of unequal learning efficiencies within the prediction of the effects of the situation variables on the relative decision costs will produce expected effects with strengths similar to the obtained effects.

Overall, the variable which had the largest impact on the relative decision costs was the subjects' decision anchoring bias. The mean BNC_i over all subjects was 0.828. This indicates that the average distance between the subjects' decision criteria and the optimal decision criteria was 82.8 percent of the optimal decision criteria. However, even given this level of overall decision anchoring bias the mean relative decision efficiency ($\overline{G}_i$) over all subjects was 0.06 (the average subject's total decision costs were 6.0 percent greater than the optimal model's total decision costs). The mean DNA_i measure over all subjects was 0.926. Considering that a value of one would indicate variable response ranges were not used, the subjects' overall decision model sensitivity was approximately that of the optimal model.

Discussion of Results

Individual decision model sensitivity. The variable response range (the DNA_i measure) was affected primarily by the cost variable. That is, those subjects within the C2 cost level demonstrated larger variable response ranges than did those subjects within the C1 cost level. The subjective adjustment limit concept may explain the difference in effect of the cost variable on the DNA_i measure. When the adjustment process involved convergence toward the standard the subjects may have perceived the standard as a limit to their adjustment process, a limit which they could have been reluctant to approach. When the adjustment process involved divergence from the standard the subjects did not have an objective value to perceive as a limit to their adjustment process. Whether a subject's adjustment process involved convergence toward or divergence from the standard depended upon the location of his initial decision

anchor relative to the optimal decision value. This factor was conditional upon the cost variable. Given the C1 level the subject's initial decision anchor was greater than the optimal decision value and the adjustment process involved convergence toward the standard. Given the C2 level the opposite held; i.e., the subject's initial decision anchor was less than the optimal decision value and the adjustment process involved divergence from the standard. As subjects' adjustments within the C1 level converged toward the standard, the subjective limit of the standard could have acted as an intervening variable which reduced the relative magnitude of the variable response range. As subjects' adjustments within the C2 cost level diverged from the standard no such subjective adjustment limit existed; therefore, the relative magnitude of the variable response range could have increased.[18]

Individual decision anchoring bias. The efficiency of information processing (BNC_i) was affected primarily by the cost variable. Subjects within the C1 cost level exhibited significantly greater anchoring bias than did subjects within the C2 cost level. These results were the reverse of those predicted by the hypotheses. The subjective limit concept again may be introduced as a possible explanation. As subjects' adjustments within the C1 cost level converged toward the standard, the subjective adjustment limit of the standard could have acted as an intervening variable which increased the level of anchoring bias. As subjects' adjustments within the C2 cost level diverged from the standard no such subjective adjustment limit existed, thus the level of anchoring bias could have decreased.[19]

Individual long-run decision efficiency. The support obtained for the hypotheses concerning the decision efficiency variable would suggest that unequal learning efficiency did not have a significant effect on the relative decision costs. The majority of the unequal learning efficiency occurred between the levels of the cost variable (the most significant effect, decision anchoring bias, was greater within the C1 cost level than within the C2 level). A closer examination of both the simulated and the obtained cost variable effects on the G_1 variable indicated that the obtained effects were not as strong as the simulated effects. The simulated effects may be adjusted for unequal learning efficiency by assuming that the effects of decision costs within the C1 cost level were increased by a factor of two (relative to the C2 cost level). After this adjustment the simulated cost variable effects have similar strengths as the obtained effects.[20]

The simulated and obtained distribution by cost variable interactions involving the relative decision costs had similar relationships between their strengths; the effects of the obtained interaction were not as strong as the effects of the simulated interaction. Again, if the simulated effects are adjusted for unequal learning efficiency, then the simulated distribution by cost variable interaction has a strength similar to that of the obtained effects.[21]

Limitations

There are several possible limitations involving the experimental environment. First, the precision of subject performance feedback during the training phase could be a limitation. The results obtained in this study might be modified substantially if such accurate feedback was not

employed. The lack of decision performance difference between the levels of the available information variable could be a direct result of this feedback; i.e., the accuracy of the performance feedback and its relationship with the optimal model may have replaced the need for such additional statistical information.

Second, the background of the subjects in relation to the experimental task is a possible limitation. Although the subjects received training in the experimental task, the primary source of their knowledge concerning standard cost variance investigation may come from the college classroom. Consequently, if they were not taught (within the classroom) that situations exist in which investigation decision values are located relatively close to the standard, then greater decision anchoring bias within these situations could be the result of the lack of such knowledge. This suggests the possibility of an availability bias (Tversky and Kahneman, 1973). However, to the extent a manager must learn from his own experiences, such a bias could exist in the real world.

Another limitation involves the selection of the levels of the situation variables. Only specific combinations of variable levels were studied within this research whereas an infinite number of combinations are possible. Different variable levels and different variable manipulations would create a difference in the experimental environment which could produce results other than those obtained in this study.

Implications for Accounting

Value of additional information. The manipulation of the information variable involved the quantity of information contained in the available information set, specifically the presence or absence of various distri-

bution information items. The results indicated that the information variable did not have a significant effect upon the relative individual decision costs. An implication of this result concerns the net benefit (for the company) of providing the additional information within the expanded information level. The additional information within an actual environment is not costless. Consequently, if such information is to be provided, other things being equal, the net benefit of such an action should be positive. Within this research the lack of a significant information variable effect implies that the net benefit of providing additional information may not be positive. However, it should be noted that the lack of an information variable effect could be the result of either: 1) that the subjects within the reduced information level were able to estimate (with relative efficiency) the missing information as a result of their training experiences with the decision task or 2) that the subjects within the expanded information level did not utilize the additional information efficiently.

General standard setting process. Another implication of this research concerns the general standard setting process. The standard used within this research may be conceived of as a type of decision behavior limit. Decision anchoring bias when the adjustment process diverges from the standard could be the result of the attraction of the standard that restrains the individual from making a complete (divergent) adjustment to the optimal decision value. Decision anchoring bias when the adjustment process converges toward the standard could be the result of the repelling force of the standard, subjectively limiting a complete (convergent) adjustment to the optimal decision value.

The question of whether decision makers could learn (either through training or experience) to reduce the decision biases implied by the decision behavior limit concept remains unanswered. An alternative approach, however, involves the standard setting process itself. Previous research involving the nature of standards (e.g., strict standards, currently attainable standards, lax standards) has primarily dealt with the standard's motivational affects. Other things being equal, the nature of the standard may affect the decision behavior limit biases. Within situations requiring divergent adjustment, lax standards (which have values greater than the mean of the in-control state) may reduce divergent decision anchoring bias. Within situations requiring convergent adjustment, strict standards (which have values less than the mean of the in-control state) may reduce convergent decision anchoring bias.

FOOTNOTES

[1]Some research on this problem has followed. Magee (1976) and Magee and Dickhaut (1978) investigate possible effects of manager performance measures upon manager variance investigation decision heuristics.

[2]An in-control distribution concerns statistical congruence of production output and planned output in terms of controllable resource utilization.

[3]Two theoretical descriptions of TSD are presented by Green and Swets (1974) and Egan (1975); general surveys of the TSD theory are presented by Coombs et al. (1970), Watson (1973), and Pastore and Scheirer (1974).

[4]These extensions to conceptual processes have included numerical processing (Lieblich and Lieblich, 1969; Hammerton, 1970; Weissman et al., 1975), medical diagnosis (Lusted, 1969; Lusted, 1971; Swets, 1972), conceptual judgement (Ulehla et al., 1967a; Ulehla et al., 1967b), and memory (Bernabach, 1967; Banks, 1970).

[5]For example, $P(Yes|sn) = f(Yes|sn)/f(sn)$ where $f(\cdot)$ denotes frequency of occurance for the event in parentheses. Since the event outcomes are both exhaustive and mutually exclusive, $P(No|sn) = 1 - P(Yes|sn)$. A similar procedure applies for the remaining conditional probabilities, $P(Yes|n)$ and $P(No|n)$.

[6]One set of TSD models assumes that both conditional probability distributions are Gaussian. The TSD parameters used in this study assume equal variance normal distributions. Such an assumption is not necessary to employ TSD. Egan (1975) demonstrates the use of TSD with exponential distributions, chi-square distributions, Bernoulli distributions, and Poisson distributions. Grier (1971) developed nonparametric measures of discriminability and decision criteria.

[7]Some other information processing and decision rule biases identified thus far have been labeled as a representative heuristic (Tversky and Kahneman, 1971; Kahneman and Tversky, 1972; Swieringa et al., 1976) and an availability heuristic (Tversky and Kahneman, 1973).

[8]Three subject selections criteria were applied: 1) the subject must have completed an intermediate-level managerial accounting course, 2) the subject must have completed an introductory-level statistics course, and 3) the subject must have earned an overall grade point average (GPA) of at least 2.0 on a 4.0 scale.

[9]The geometric intersection point of the two states' distribution curves is arbitrarily employed as the initial decision anchor (any

point of central tendency would be equally valid). The location of this initial decision anchor is dependent upon the level of the distribution variable.

[10]The magnitude of the linear movement used in the simulation is is 50 percent of the distance between the initial decision anchor and the appropriate optimal model decision cutoff. The 50 percent adjustment value is arbitrarily selected. The assumption of an equal 50 percent adjustment over the treatment conditions is not critical to the conceptual development; the objective is to facilitate a simple operationalization of the anchoring and adjustment heuristic.

[11]Given any dichotomous variable (e.g., information, distribution, or cost) and eight treatment conditions, four conditions will include the variable at one level and four conditions will include the variable at the second level.

[12]The procedure for the cost variable resulted in:

$$\frac{\overline{BNC}|C2 - \overline{BNC}|C1}{.5\sqrt{S_1^2 + S_2^2}} = .14495/.02436 = 5.9503.$$

[13]The procedure for the cost variable resulted in:

$$\frac{\overline{G}_i|C2 - \overline{G}_i|C1}{.5\sqrt{S_1^2 + S^2}} = .033/.0095 = 3.5258.$$

[14]The procedure for the cost by distribution variables resulted in:

$$\frac{(\overline{G}_i|S1,C2 - \overline{G}_i|S2,C2) - (\overline{G}_i|S1,C1 - \overline{G}_i|S2,C1)}{\sqrt{S_1^2 + S_2^2 + S_3^2 + S_4^2}}$$

$$= .0291/.0136 = 2.1397.$$

[15]Additional information, not analyzed in this paper, were collected from the subjects in the form of a heuristics questionnaire. For more detail see Brown (1978).

[16]Ideally, individual intelligence should be measured using some validated instrument (e.g., the Wesman Personnel Classification Test or the Wechsler Adult Intelligence Scale). Due to resource limitations, however, subject grade point average (GPA) was used as a surrogate for such a measure.

[17]The assignment process involved two procedures. First, the assignment to the cost variable levels was by the week in which the subject participated in the experiment. Those subjects who participated during the first week were assigned to the C1 cost level, and those subjects who participated during the second week were assigned to the C2 cost level. Second, the assignment to the information variable and the distribution variable levels was by random selection based upon a random number table.

[18]The higher (statistical) moments of the DNA_i measure given the levels of the cost variable were consistent with the concept of a subjective adjustment limit. Such a limit should have had the effect of reducing the variance of this measure. The test of the variances indicated that $(DNA_i|C1)$ had a significantly smaller variance than $(DNA_i|C2)$. The subjective limit also should have had the effect of skewing the measure away from those values which indicated larger variable response ranges. The third moment (as expressed by the coefficient of skewness) of the DNA_i measure indicated that: 1) the skewness of the $(DNA_i|C1)$ distribution was positive (skewed away from values which indicated larger variable response ranges), and 2) the skewness of the $(DNA_i|C2)$ distribution was negative (skewed toward values which indicated larger variable response ranges).

[19]The higher (statistical) moments of the BNC_i measure given the levels of the cost variable were consistent with the concept of a subjective adjustment limit. The difference in variances of the BNC_i measure was due to the difference in the ranges of the measure. The range of $(BNC_i|C1)$ was 4.67 and the range of $(BNC_i|C2)$ was 1.57. The subjective adjustment limit should have had the effect of skewing the measure away from those value which indicated lower levels of anchoring bias. The third moment (as expressed by the coefficient of skewness) of the BNC_i measure indicated that: 1) the skewness of the $(BNC_i|C1)$ distribution was positive (skewed away from values which indicated lower levels of anchoring bias), and 2) the skewness of the $(BNC_i|C2)$ distribution was negative (skewed toward values which indicated lower levels of anchoring bias).

[20]Note that for the obtained results:

$$\overline{G}_i|C2 \; / \; \overline{G}_i|C1 = 1.61,$$

whereas for the expected results:

$$E(\overline{G}_i|C2) \; / \; E(\overline{G}_i|C1) = 3.27.$$

The affect of the unequal learning efficiency adjustment would give expected results of:

$$E(\overline{G}_i|C2) \ / \ 2E(\overline{G}_i|C1) = 1.60.$$

[21]Note that for the obtained results:

$$\frac{(\overline{G}_i|S1,C2) - (\overline{G}_i|S2,C2)}{(\overline{G}_i|S1,C1) - (\overline{G}_i|S2,C1)} = 3.15,$$

whereas for the expected results:

$$\frac{E(\overline{G}_i|S1,C2) - E(\overline{G}_i|S2,C2)}{E(\overline{G}_i|S1,C1) - E(\overline{G}_i|S2,C1)} = 8.74.$$

The affect of the unequal learning efficiency adjustment would give expected results of:

$$\frac{E(\overline{G}_i|S1,C2) - E(\overline{G}_i|S2,C2)}{2[E(\overline{G}_i|S1,C1) - E(\overline{G}_i|S2,C1)]} = 4.37.$$

BIBLIOGRAPHY

Alpert, M., and Raiffa, H. "A Progress Report on the Training of Probability Assessors." Unpublished manuscript, Harvard University, 1968.

Appelbaum, M. I., and Cramer, E. M. "Some Problems in the Nonorthogonal Analysis of Variance." Psychological Bulletin, 81 (1974), 335-43.

Banks, W. P. "Signal Detection Theory and Human Memory." Psychological Bulletin, 74 (1970), 81-99.

Bernbach, H. A. "Decision Processes in Memory." Psychological Review, 74 (1967), 462-80.

Bierman, H.; Fouraker, L. E.; and Jaedicke, R. K. "A Use Probability and Statistics in Performance Evaluation." The Accounting Review, 36 (1961), 409-17.

Brown, C. E. Human Information Processing for Decisions to Investigate Cost Variances. Doctoral dissertation, University of Florida, 1978.

Coombs, C. H.; Dawes, R. M.; and Tversky, A. Mathematical Psychology: An Elementary Introduction. Englewood Cliffs, N.J.: Prentice-Hall, Inc., 1970.

Dittman, D. A., and Prakash, P. "Cost Variance Investigation: Markovian Control of Markov Processes." Journal of Accounting Research, 16 (1978), 14-25.

Dyckman, T. R. "The Investigation of Cost Variances." Journal of Accounting Research, 7 (1969), 215-44.

Egan, J. P. Signal Detection Theory and ROC Analysis. New York: Academic Press, Inc., 1975.

Green, D. M., and Swets, J. A. Signal Detection Theory and Psychophysics. New York: Robert E. Krieger Publishing Co., 1974.

Grier, J. B. "Nonparametric Indexes for Sensitivity and Bias: Computing Formulas." Psychological Bulletin, 75 (1971), 424-9.

Hammerton, M. "An Investigation into Changes in Decision Criteria and Other Details of a Decision-Making Task." Psychonomic Science, 21 (1970), 203-4.

Jacobs, F. H. "An Evaluation of the Effectiveness of Some Cost Variance Investigation Models." Journal of Accounting Research, 16 (1978), 190-203.

Juers, D. A. "Statistical Significance of Accounting Variances." Management Accounting, 49 (1967), 20-5.

Kahneman, D., and Tversky, A. "Subjective Probability: A Judgement of Representativeness." Cognitive Psychology, 5 (1972), 430-54.

Kaplan, R. S. "Optimal Investigation Strategies with Imperfect Information." Journal of Accounting Research, 7 (1969), 32-43.

________. "The Significance and Investigation of Cost Variances: Survey and Extensions." Journal of Accounting Research, 13 (1975), 311-37.

Koehler, R. W. "The Relevance of Probability Statistics to Accounting Variance Control." Management Accounting, 50 (1968), 35-41.

Lewis, C., and Keren, G. "You Can't Have Your Cake and Eat It Too: Some Considerations of the Error Term." Psychological Bulletin, 84 (1977), 1150-4.

Lieblich, A., and Lieblich, I. "Arithmetical Estimation Under Conditions of Different Payoff Matrices." Psychonomic Science, 14 (1969), 87-8.

Luh, F. "Controlled Cost: An Operational Concept and Statistical Approach to Standard Costing." The Accounting Review, 43 (1968), 123-32.

Lusted, L. B. "Perception of the Roentgen Image: Applications of Signal Detectability Theory." Radiological Clinics of North America, 3 (1969), 435-45.

________. "Signal Detectability and Medical Decision-Making." Science, 171 (1971), 1217-9.

Magee, R. P. "A Simulation Analysis of Alternative Cost Variance Investigation Models." The Accounting Review, 51 (1976), 529-44.

________, and Dickhaut, J. W. "Effects of Compensation Plans on Heuristics in Cost Variance Investigations." Journal of Accounting Research, 16 (1978), 294-314.

Pastore, R. E., and Scheirer, C. J. "Signal Detection Theory: Considerations for General Application." Psychological Bulletin, 81 (1974), 945-58.

Probst, F. R. "Probabilistic Cost Controls: A Behavioral Dimension." The Accounting Review, 46 (1971), 113-8.

Scheffe, H. The Analysis of Variance. New York: John Wiley and Sons, Inc., 1959.

Slovic, P. "From Shakespeare to Simon: Speculations--and Some Evidence--About Man's Ability to Process Information." Oregon Research Institute Bulletin, 12 (1972).

________, and Lichtenstein, S. "Comparison of Bayesian and Regression Approaches to the Study of Information Processing in Judgement." Organizational Behavior and Human Performance, 6 (1971), 649-744.

Snowball, D., and Brown, C. "Decision-Making Involving Sequential Events: Some Effects of Disaggregated Data and Dispositions Toward Risk." Decision Sciences, forthcoming.

Swets, J. A. "Signal Detection in Medical Diagnosis." In Computer Diagnosis and Diagnostic Methods, J. A. Jacquez (Ed.). Springfield, IL: C. C. Thomas, 1972.

Swieringa, R. J.; Gibbins, M.; Larsson, L.; and Sweeney, J. L. "Experiments in the Heuristics of Human Information Processing." Journal of Accounting Research: Supplement on Studies on Human Information Processing in Accounting, 14 (1976), 159-87.

Tversky, A., and Kahneman, D. "Belief in the Law of Small Numbers." Psychological Bulletin, 76 (1971), 105-10.

________. "Availability: A Heuristic for Judging Frequency and Probability." Cognitive Psychology, 5 (1973), 207-32.

________. "Judgement Under Uncertainty: Heuristics and Biases." Science, 185 (1974), 1124-31.

Ulehla, Z. J.; Canges, L.; Wackwitz, F. "Signal Detectability Theory Applied to Conceptual Discrimination." Psychonomic Science, 8 (1967a), 221-2.

________. "Integration of Conceptual Information." Psychonomic Science, 8 (1967b), 223-4.

Watson, C. S. "Psychophysics." In Handbook of General Psychology, B. B. Wolman (Ed.). New York: Prentice-Hall, Inc., 1973.

Weissman, S. M.; Hollingworth, S. R.; Baird, J. C. "Psychophysical Study of Numbers: III. Methodological Applications." Psychological Research, 38 (1975), 97-115.

Zannetos, Z. A. "Standard Cost as a First Step to Probabilistic Control: A Theoretical Justification, and Extension and Implications." The Accounting Review, 39 (1964), 296-304.

AMSECO
Metal Folding Chair Assembly Department
Labor Efficiency Variance Report For Job 5247

Standard Minutes Allowed Per Chair	Actual Minutes Incurred Per Chair	Labor Efficiency Variance Per Chair	Total Chairs Produced
36.0	44.0	-8.0	200

The Costs Associated With Investigation Are:

If Your Investigation Decision Is	And If The Assembly Line State Is	Then Your Costs Are Investigation	Production	Total
Yes	In-Control	$ 28.33	$ 0.00	$ 28.33
Yes	Out-Of-Control	$ 90.00	$ 0.00	$ 90.00
No	In-Control	$ 0.00	$ 0.00	$ 0.00
No	Ou-Of-Control	$ 0.00	$ 175.00	$ 175.00

##

Please answer the following questions placing your answers on the answer sheet:

A. Would you investigate this reported variance /circle the appropriate response on the answer sheet/

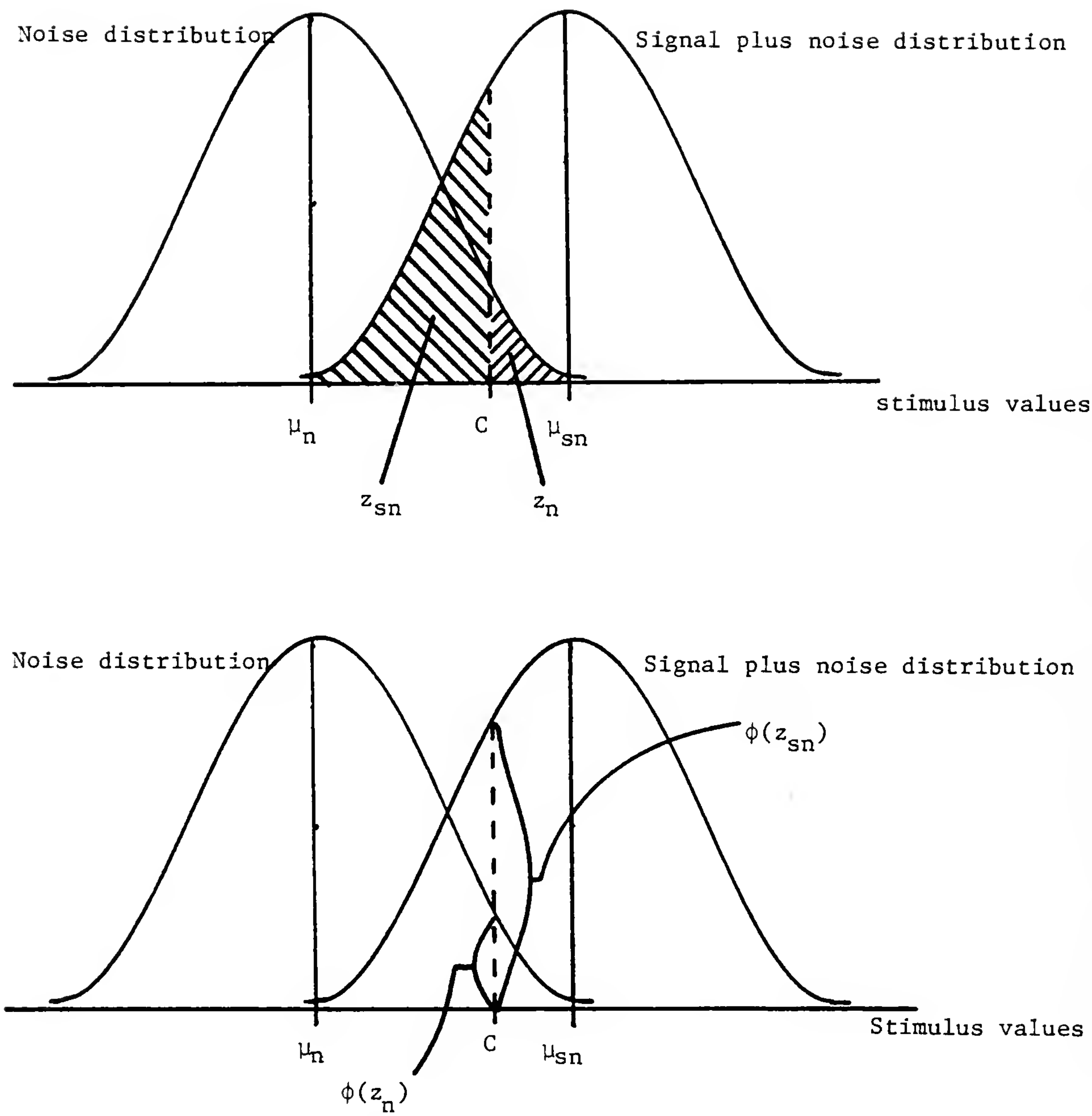
NO YES

B. How strongly do you feel about your decision /select a number between 0 and 100 which indicates the strength of your feeling and place this number on the answer sheet/

```
0    10   20   30   40   50   60   70   80   90   100
*    *    *    *    *    *    *    *    *    *    *
***************************************************
*    *    *    *    *    *    *    *    *    *    *
*                        *                        *
Uncertain           Reasonably               Almost
                     Certain                 Certain
```

APPENDIX A

VARIANCE INVESTIGATION DECISION TRIAL



μ_n = mean of the noise distribution
μ_{sn} = mean of the signal plus noise distribution
C = subjective decision cutoff

FIGURE 1

GRAPHIC REPRESENTATION OF THE TSD PARAMETERS

TABLE 1

GENERAL RESEARCH DESIGN IN TERMS OF EXPERIMENTAL VARIABLES

	Dependent Variables		
Independent Variables	Individual Long-Run Decision Efficiency	Individual Decision Model Sensitivity	Individual Decision Criteria
Contents of the available information set	X	X	X
Structure of the decision situation:			
Statistical relationships	X	X	X
Decision outcome relationships	X	X	X
Individual decision model sensitivity	X		

Note: An "X" within a cell indicates that the relationship of the variables concerned are included within the experimental design.

TABLE 2

MODEL COMPARISON PROCEDURE RESULTS FOR THE DNA_i DEPENDENT VARIABLE

Model	SSe	d.f.(F)	F
Full[d]	1.1753	11,74	2.03[b]
Without 3-way interaction	1.1758	1,74	0.03
Without distribution x cost interaction	1.2105	1,75	2.22
Without information x distribution interaction	1.1783	1,75	0.16
Without information x cost interaction	1.1758	1,75	0.00
Without information[e]	1.2140	1,78	0.01
Without distribution[e]	1.2269	1,78	0.84
Without cost[e]	1.4522	1,78	15.31[a]

F VALUES ASSOCIATED WITH THE SOURCES OF THE REDUCED MODEL

Source	d.f.	F
Cost	1,80	15.52[a]
Intrinsic motivation	1,80	3.55[c]
Extrinsic (non-monetary) motivation	1,80	1.38
Extrinsic (monetary) motivation	1,80	0.07
GPA	1,80	0.14

MEANS AND VARIANCES ASSOCIATED WITH THE SIGNIFICANT VARIABLE

Variable Level	N	Mean	Variance
C1	47	0.9726	0.0091
C2	39	0.8696	0.0234

[a] $p<.01$ [b] $p<.05$ [c] $p<.10$

[d] The F value associated with the full model is the test of the full model and not a model comparison test.

[e] The test of this model assumes the effects of those interactions that include this variable are equal to zero.

TABLE 3

MODEL COMPARISON PROCEDURE RESULTS FOR THE BNC_1 DEPENDENT VARIABLE

Model	SSe	d.f.(F)	F
Full[c]	38.249	11,74	2.35[b]
Without 3-way interaction	38.510	1,74	0.51
Without distribution x cost interaction	39.291	1,75	1.52
Without information x distribution interaction	38.543	1,75	0.06
Without information x cost interaction	38.624	1,75	0.22
Without information[d]	39.895	1,78	0.91
Without distribution[d]	39.607	1,78	0.34
Without cost[d]	42.778	1,78	6.61[b]

F VALUES ASSOCIATED WITH THE SOURCES OF THE REDUCED MODEL

Source	d.f.	F
Cost	1,80	6.88[b]
Intrinsic motivation	1,80	2.61
Extrinsic (non-monetary) motivation	1,80	0.04
Extrinsic (monetary) motivation	1,80	7.79[a]
GPA	1,80	4.90[b]

MEANS AND VARIANCES ASSOCIATED WITH THE SIGNIFICANT VARIABLE

Variable Level	N	Mean	Variance
C1	47	1.0046	0.96602
C2	39	0.6147	0.10326

[a] $p<.01$ [b] $p<.05$

[c] The F value associated with the full model is the test of the full model and not a model comparison test.

[d] The test of this model assumes the effects of those interactions that include this variable are equal to zero.

TABLE 4

MODEL COMPARISON PROCEDURE RESULTS FOR THE G_1 DEPENDENT VARIABLE

Model	SSe	d.f.(F)	F
Full[b]	0.0809	12,73	12.08[a]
Without 3-way interaction	0.0811	1,73	0.17
Without distribution x cost interaction	0.0895	1,74	7.71[a]
Without information x distribution interaction	0.0812	1,74	0.09
Without information x cost interaction	0.0814	1,74	0.26
Without information[c]	0.0826	1,76	1.05
Without distribution[c]			
Without cost[c]			

F VALUES ASSOCIATED WITH THE SOURCES OF THE REDUCED MODEL

Source	d.f.	F
Distribution	1,70	0.51
Cost	1,70	2.56
Distribution x cost	1,70	7.92[a]
DNA_1	1,70	88.76[a]
Intrinsic motivation	1,70	2.40
Extrinsic (non-monetary) motivation	1,70	0.00
Extrinsic (monetary) motivation	1,70	1.71
GPA	1,70	2.39

MEANS AND VARIANCES ASSOCIATED WITH THE SIGNIFICANT VARIABLES

Variable Level	N	Mean	Variance
S1, C1	24	0.0504	0.00229
S1, C2	20	0.0921	0.00371
S2, C1	23	0.0430	0.00097
S2, C2	19	0.0575	0.00375

[a] $p<.01$

[b] The F value associated with the full model is the test of the full model and not a model comparison test.

[c] The test of this model assumes the effects of those interactions that include this variable are equal to zero.

Faculty Working Papers

TWO VIEWS ON SOVIET COLLECTIVIZATION OF AGRICULTURE

James R. Millar, Professor, Department of Economics

#615

College of Commerce and Business Administration
University of Illinois at Urbana-Champaign